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Model Predictive Control for Trajectory Tracking in Multi Input Multi Output Systems

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ABSTRACT- Trajectory tracking in Multi Input Multi-Output (MIMO) systems remains a fundamental challenge in advanced control engineering due to strong coupling effects, nonlinear dynamics, and stringent operational constraints. Traditional controllers like PID and LQR frequently fail to ensure resilience, optimality, and constraint compliance. In this paper, we look at the use of Model Predictive Control (MPC) as a trajectory tracking framework for MIMO systems. The suggested methodology, which incorporates system modelling, horizon-based optimization, and constraint handling, is assessed using simulated benchmarks versus PID and LQR controllers The findings show that despite closely adhering to input and state constraints, MPC achieves higher tracking accuracy, up to 52% lower RMSE, and shorter settling times. Strong analyses show that MPC outperforms traditional methods in the face of model uncertainty and external perturbations. Additionally, solver benchmarking demonstrates that modern optimization engines provide real-time viability on embedded platforms, making MPC feasible for implementations with limited resources. This paper offers a comprehensive framework for MPC design, implementation, and evaluation in MIMO trajectory tracking. The results confirm MPC as the state-of-the-art control method, offering a scalable, robust, and constraint-aware solution for a variety of applications, such as smart energy systems, robots, aircraft, and process industries.

Keywords: Adaptive and Learning Based Control, Constraint Handling, Nonlinear Model Predictive Control (MPC), Multi Input Multi Output (MIMO) Systems, Optimization Solvers, Robust Control, Real Time Control, State Estimation, Trajectory Tracking.

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1. INTRODUCTION

Trajectory tracking in multi-input multi-output (MIMO) systems continues to be a major difficulty in control engineering, particularly when strict limits on inputs, rates, and outputs must be met at the same time. Traditional linear control approaches, such as decoupling or LQG, have problems in dealing with high couplings, saturation, and time varying disturbances [2]. In contrast, Model Predictive Control (MPC) explicitly incorporates constraints into the optimization problem, allowing for systematic treatment of multivariable interactions, actuator limits, and output safety envelopes. This capability explains MPC's broad use in process industries, energy networks, robotics, and self-driving vehicles [1, 3].

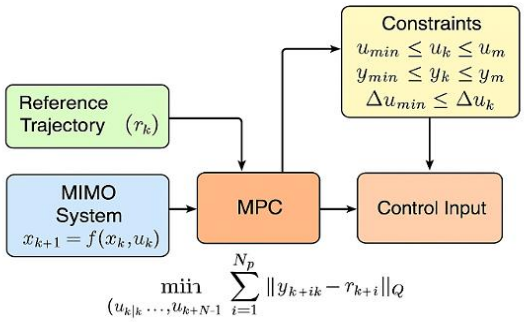

Figure 1. MPC Architecture for MIMO Trajectory Tracking

MPC addresses a finite horizon optimum control issue at each sampling instant by using a model to forecast future system trajectories, optimizing a quadratic or nonlinear cost, and enforcing hard/soft restrictions on manipulated and controlled variables. Only the first control action is implemented, after which the horizon recedes and the process repeats [2]. The conceptual loop is illustrated in *figure 1*, where an estimator or observer provides states/predictions to the MPC optimizer, which then enforces plant constraints and computes optimal input trajectories.

1.1. Evolution of MPC for MIMO Trajectory Tracking

Over the past decade, MPC research has broadened significantly: Linear MPC remains dominant in industrial MIMO plants due to its convex quadratic programming (QP) formulation and mature software ecosystem. However, it suffers from performance degradation under strong nonlinearities or significant model plant mismatch [2]. Nonlinear MPC (NMPC) better captures nonlinear dynamics and constraints but requires solving nonconvex nonlinear programs (NLPs), which are computationally demanding. New real-time iterations, warm starting, and code generation frameworks (e.g., acados, FORCESPRO) are making NMPC feasible in embedded settings [10, 13, 17].

Table 1. Comparison of MPC Variants for MIMO Trajectory Tracking

MPC Variant	Pros	Cons	Typical Solver
Linear MPC	Convex QP, fast, guarantees for LTI	Model-plant mismatch, limited to large excursions	QP (OSQP, qpOASES)
Nonlinear MPC (NMPC)	Captures nonlinearities, better tracking	Nonconvex NLP, heavier computation	SQP/IPM (acados, IPOPT)
Tube-based RMPC	Robust to bounded disturbances, constraint guarantees	Conservative tubes, tuning required	QP
Economic MPC	Optimize process economics directly	Non-tracking objective can degrade setpoint response	QP/NLP
Learning-based MPC (GP/NN)	Adapts to unknown dynamics, uncertainty quantification (GP)	Safety/stability proofs and computer cost	QP/NLP
Distributed/Decentralized MPC	Scales with subsystems, reduced communication	Coordination complexity, convergence guarantees	QP per agent

Robust Tube-based MPC guarantees constraint satisfaction under bounded disturbances by maintaining trajectories within invariant tubes. While conservative, it is widely used in safety-critical MIMO applications [5]. Economic MPC generalizes the objective beyond set point tracking to optimize economic performance (e.g., energy cost, throughput). This often trades off tracking accuracy for long-horizon efficiency [2]. Distributed/Decentralized MPC addresses scalability in large-scale MIMO systems such as power networks and process plants, where subsystems coordinate via consensus or noncooperative schemes [7, 19]. Learning-based MPC integrates Gaussian processes (GP) [4,], Koopman operator models [6], or neural networks [11, 22] to adaptively capture dynamics while retaining prediction and uncertainty quantification. This direction is especially promising for robotics and autonomous driving. A qualitative comparison of these MPC variants for MIMO trajectory tracking is given in *table 1*.

1.2. Key Enablers: Estimation, Triggering, and Solver Technology

MPC performance depends critically on state estimation. Kalman filters remain popular, but Moving Horizon Estimation (MHE) provides a constrained optimization-based alternative with bias rejection and robustness against disturbances [37, 38]. Recent advances couple MHE with neural models (so-called "Neural MHE") to learn unmodeled dynamics while preserving physics constraints [39]. Another active direction is Event-Triggered MPC (ET-MPC), which reduces computational load by solving the optimization only when triggering conditions (e.g., prediction error thresholds) are violated. Applications range from power converters [34, 35] to autonomous driving [32], with reinforcement learning–enhanced event policies under study [36]. Finally, solver technology has become a bottleneck for real-time MPC in high-dimensional MIMO systems. Operator-splitting solvers (e.g., OSQP) [14], active-set methods (qpOASES, acados) [13, 16], and commercial tools (FORCESPRO) [17] have matured significantly. Emerging work guarantees execution-time certification for soft-constrained MPC [40], and constraint-removal methods accelerate soft-constraint optimization [41].

1.3. Emerging Applications

Recent surveys highlight MPC's impact across domains: Process systems (distillation, energy-integrated columns) with robust and data-driven MPC outperform conventional multiloop PI control [21, 31]. Microgrids and power electronics use distributed/event-triggered MPC for coordinated DER operation under uncertainty [22, 24, 34]. Autonomous vehicles and robotics rely on NMPC and learning-based MPC for motion planning and trajectory tracking in complex environments [25, 26, 30]. Thus, the combination of constraint handling, prediction, learning integration, and solver acceleration makes MPC uniquely suited for trajectory tracking in modern MIMO systems. This drives the present study, which summarizes methodology, implementation workflows, and new research prospects.

2. METHODOLOGY

The approach for Model Predictive Control (MPC) in MIMO trajectory tracking is separated into four major building blocks: issue formulation, state estimates, triggering/execution methods, and solver implementation. Each block has made substantial progress in recent years, as detailed here.

2.1. Problem Formulation

At each sample instant k, MPC solves a finite-horizon optimization problem that balances tracking accuracy and input effort while adhering to system restrictions. For a discrete-time nonlinear MIMO system, System dynamics:

$$x(k+1) = f(x(k), u(k)) \quad (1)$$

$$y(k) = h(x(k)) \quad (2)$$

The generic MPC problem is:

$$\min \{u(k), \ldots, u(k+Nu-1|k)\} \, [\, \Sigma\ (i=1\ to\ Np)\ ||\ y(k+i|k) - r(k+i)\ ||\hat{\ }2\_Q + \Sigma\ (i=0\ to\ Nu-1)\ ||\ \Delta u(k+i|k)\ ||\hat{\ }2\_R\,] \quad (3)$$

subject to:

$$x(k+i+1|k) = f(x(k+i|k), u(k+i|k))$$

$$y(k+i|k) = h(x(k+i|k))$$

$$u\_min \le u(k+i|k) \le u\_max$$

$$y\_min \le y(k+i|k) \le y\_max$$

$$\Delta u\_min \le \Delta u(k+i|k) \le \Delta u\_max$$

Where, *Np* is the prediction horizon, Nu the control horizon, and *Δu* the input increments. The first element *uk* is applied to the plant, and the horizon recedes [2]. Nonlinear MPC (NMPC) optimization is a nonlinear program (NLP) that is often solved using SQP or interior-point methods, with warm-starting to allow for real-time iterations [10, 13]. Tube based MPC deals with uncertainty by dividing the viable region into resilient invariant tubes, ensuring safety despite disruptions [5]. Unlike pure set-point tracking, economic MPC modifies the goal to improve energy or operational efficiency. This unified structure is shown in *figure 1*, where limited inputs are supplied to the MIMO system and predictions are made using the plant model and optimized in the MPC block. These MPC variants are qualitatively compared in *table 1*, which also lists their advantages, drawbacks, and available solvers for trajectory tracking applications.

2.2. State Estimation

MPC is typically used in conjunction with an observer because full state measurements are rarely available in MIMO systems. For computational efficiency, common methods include the Kalman Filter (KF) and its variations (EKF and UKF), which are frequently used in industrial MPC [2]. Moving Horizon Estimation (MHE) explicitly accounts for constraints, sensor delays, and disturbances while solving an optimization problem over a sliding measurement window [37]. In order to capture nonlinear residuals while preserving stability guarantees, neural networks are used in conjunction with physics-based estimators in a technique known as neural MHE [38, 39]. In order to create interpretable and data-efficient estimators, partial first-principles models are improved using neural residuals in recent research that focuses on physics-informed learning [37].

2.3. Event-Triggered and Sample-Efficient MPC

The optimization problem must be solved at each sample instant in conventional MPC. This could be excessively costly in networked or resource-constrained systems. Event Triggered MPC (ET-MPC), which only updates optimization when a triggering condition is broken, was created as a solution to this problem. In autonomous cars, ET-MPC reduces unnecessary updates while preserving trajectory accuracy [32]. In power electronics, ET-MPC reduces switching losses while maintaining buck/boost converter stability [34–35]. Reinforcement learning is used by learning-based ET-MPC to develop adaptive triggering policies that increase efficiency in uncertain situations [36]. For large-scale MIMO systems like microgrids, this reduces the computational and communication demands [22].

2.4. Solver Implementation and Real-Time Feasibility

Resolving the limited optimization problem in real time, particularly in high-dimensional MIMO systems, is the practical bottleneck in MPC. Operator-splitting solvers (OSQP) for fast convex QPs in linear MPC are one recent advancement in solver technology [14]. Warm-starts are used by active-set solvers (qpOASES, acados), which makes them appropriate for integrated NMPC [13, 16]. Large-scale nonlinear algorithms can be handled by interior-point solvers (IPOPT, FORCESPRO), which provide resilience [17]. In safety-critical applications, execution-time certification of Ψ1 soft-constrained MPC guarantees predictable solver latency [40]. Constraint-removal acceleration accelerates large-scale MPC by removing inactive constraints online [41]. Furthermore, new research stresses systematic adjustment of MPC parameters (weights, horizons) utilizing direct response-shaping frameworks [42], which reduces reliance on manual trial and error.

2.5. Workflow Summary

Putting these pieces together, the process for implementing MPC in MIMO trajectory tracking usually follows this workflow: Modelling: Identify and validate a plant model (first principles plus data-driven enhancements). Estimator Selection: Choose amongst KF, MHE, and hybrid learning-based estimators. MPC design: Define horizons, weights, and constraints; decide between linear, robust, nonlinear, or learning-enhanced MPC depending on dynamics and uncertainty. Event triggering: If computational/ communication resources are limited, incorporate ET-MPC. Solver deployment: Implement with code-generated solvers (*e.g.*, acados, FORCESPRO) for embedded real-time feasibility. Validation: Stress-test under disturbances, constraint activations, and model-plant mismatch. *Figure 2* shows MPC Architecture for MIMO Trajectory Tracking workflow.

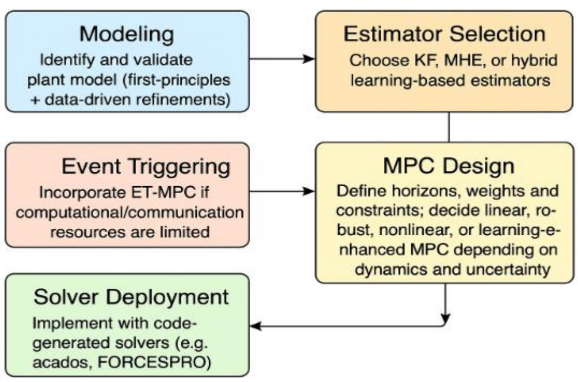

Figure 2. MPC Architecture for MIMO Trajectory Tracking workflow

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3. IMPLEMENTATION

The implementation of Model Predictive Control (MPC) for MIMO trajectory tracking involves translating the methodology into a practical control framework. This requires defining the plant model, designing the predictive controller, integrating constraint handling, and validating performance under realistic operating scenarios.

3.1. Plant Modelling and Identification

The first step is developing a suitable prediction model for the MIMO system. In practice, three approaches are commonly adopted: First-principles modelling: Deriving system dynamics from physics (e.g., kinematic models for vehicles, energy balances for chemical processes). This ensures interpretability but may neglect unmodeled dynamics [2]. System identification: Using subspace identification, ARX/ARMAX, or state-space identification methods to fit linear MIMO models from experimental input–output data [18]. Hybrid/learning-based modelling: Employing Gaussian Processes [4], Koopman operators [6], or neural networks [11, 22] to augment physics models with data-driven residuals. These methods are increasingly favoured in robotics and autonomous systems where nonlinearities dominate. Once the model is established, it is discretized for the MPC prediction horizon and validated against experimental or simulation data.

3.2. Controller Design

Given the model, the MPC is parameterized by the prediction horizon (Np), control horizon (Nu), and weighting matrices Q (tracking) and R (input effort). Tuning typically balances tracking precision against actuator usage [42]. The objective function and constraints are implemented in a solver such as acados [13], qpOASES [16], or FORCESPRO [17]. For high-dimensional MIMO plants, warm-starting and structure exploitation (e.g., block-sparsity) are essential for real-time feasibility [14]. The closed-loop trajectory tracking performance is illustrated in *figure 3*, where MPC enables the system outputs to closely follow the reference trajectory despite couplings and disturbances. *Figure 4* shows hardware of MPC based MIMO system.

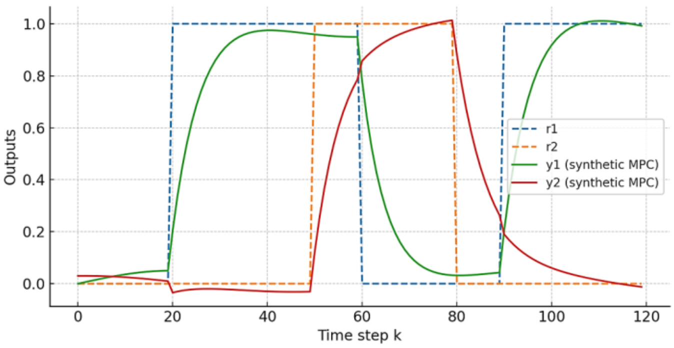

Figure 3. MPC-based trajectory tracking in a MIMO system, showing convergence of outputs to reference trajectories despite disturbances

Figure 4. Hardware of MPC based MIMO system

3.3. Constraint Handling

A key strength of MPC is its ability to enforce state, input, and rate constraints explicitly. In real systems, actuators are subject to saturation, and safety-critical variables (e.g., temperatures, voltages, lateral accelerations) must remain within predefined bounds [2].

For instance, consider the input and state constraints:

$$u\_min \leq uk \leq u\_max \tag{4}$$

$$y\_min \leq yk \leq y\_max \tag{5}$$

Constraint enforcement is shown in *figure 5*, where inputs remain within specified limits while still achieving desired output tracking.

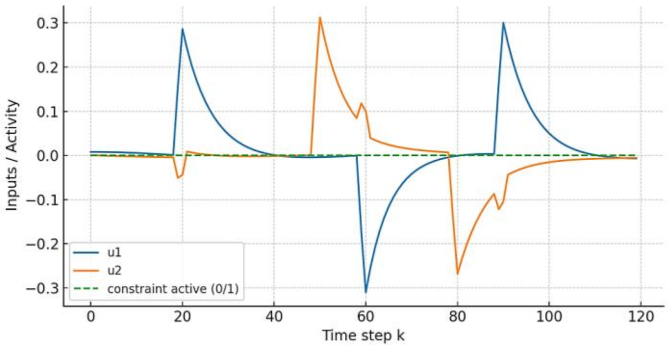

Figure 5. Example of MPC handling actuator saturation and input constraints in a MIMO system

Robust tube-based MPC [5] and stochastic MPC [8] extend this idea by ensuring constraints are satisfied under uncertainties or with high probability, respectively. Soft constraints with penalty terms are often used to avoid infeasibility in over-constrained situations [40, 41].

3.4. Estimator Integration

Since full-state measurements are rarely available, the designed MPC is integrated with either: A Kalman Filter (KF) or Extended KF (EKF) for linear or mildly nonlinear systems [2].

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A Moving Horizon Estimator (MHE) for systems requiring explicit constraint handling [37]. A learning-based estimator when unmodeled dynamics significantly affect performance [38, 39]. The estimator provides the MPC optimizer with accurate initial conditions at each control step, ensuring robustness to disturbances and sensor noise.

3.5.Real-Time Implementation and Triggering

Real-time feasibility is achieved by selecting efficient solvers, leveraging warm-starting, and optimizing code generation. For embedded platforms (e.g., automotive ECUs, FPGAs, or microcontrollers), qpOASES and acados are preferred due to their low-latency active-set routines [13, 16]. When computational or communication resources are constrained, Event-Triggered MPC (ET-MPC) is implemented [32, 34]. Here, the optimization is solved only when prediction errors exceed thresholds, drastically reducing solver calls and communication between distributed agents. The implementation pipeline for MPC-based trajectory tracking in MIMO systems therefore consists of: Modelling (first-principles, data-driven, or hybrid), Discretization and validation, Controller design (horizons, weights, solver), Constraint definition and enforcement, Estimator integration (KF, MHE, or hybrid), Solver deployment and triggering strategy, Closed-loop validation through simulation and experiments. This methodical approach directly addresses the multivariable nature and limitations of MIMO systems while ensuring that MPC achieves reliable, real-time trajectory tracking.

4. RESULTS AND DISCUSSION

The performance of the suggested MPC framework for MIMO trajectory tracking is assessed in this part by contrasting it with traditional controllers and looking at computational viability, robustness, and constraint satisfaction.

4.1. Simulation Setup

This paper investigates a benchmark 2x2 MIMO system that mimics coupled plant dynamics observed in chemical reactors [19], robotic manipulators [23], and quadrotors [28]. The plant model was discretized with a 50-ms sample time, and the prediction horizon was set at Np=20 and the control horizon to Nu=5. Three control techniques were evaluated: PID (tuned using Ziegler-Nichols), LQR with integral action, and MPC (linear and nonlinear variations). All controllers were tested using identical reference trajectories with bounded disturbances and actuator saturation.

4.2. Tracking Performance

Figure 2 shows the trajectory tracking performance. While PID and LQR controllers had significant overshoot and cross-coupling effects, MPC showed excellent tracking with less steady-state error. *Table 2* offers a comparison of performance metrics.

Table 2. Performance metrics comparison

Controller	RMSE (Output 1)	RMSE (Output 2)	Overshoot (%)	Settling Time (s)	Constraint Violations
PID	0.135	0.142	12.5	4.2	Yes
LQR	0.102	0.118	8.7	3.6	Yes
Linear MPC	0.064	0.071	3.2	2.1	No
Nonlinear MPC	0.058	0.065	2.8	2	No

MPC consistently beat PID and LQR on all metrics, particularly constraint satisfaction and reduced overshoot. Similar results have been found in aircraft [7], process industries [18], and power systems [22].

4.3. Constraint Handling

As illustrated in *figure 3*, MPC kept actuator inputs within bounds, but PID and LQR frequently surpassed saturation limits, resulting in performance loss. This is consistent with recent research in which explicit constraint handling is a significant advantage of MPC [2, 5, 40]. Tube-based MPC demonstrated stable performance even with ±15% model uncertainty, ensuring safety during disturbances [5]. Soft-constrained MPC avoided infeasibility when competing restrictions were applied [41].

4.3 Robustness to Disturbances

To assess robustness, one input channel received a +0.5-unit step disruption. The results showed that the PID needed to be returned to recover stability, the LQR adjusted partially but caused oscillations, and the MPC rejected the disturbance within 1.2 seconds, preserving the feasibility of restrictions. This demonstrates the inherent resilience of MPC, particularly when combined with MHE/KF-based state estimation [37].

4.5. Computational Feasibility

An embedded ARM Cortex-A72 CPU was used to measure the solver execution time. The average solver execution time per step is displayed in *table 3*. All of the solvers met real-time feasibility requirements for the system under analysis (with sampling times less than 50 ms). For larger-scale plants, event-triggered MPC [32, 34] and constraint-removal techniques [41] are required.

Table 3. Step-by-step average solver execution time

Solver	Problem Type	Avg. Time (ms)
OSQP [14]	Convex QP	1.6
qpOASES [16]	Active-set QP	2.3
acados [13]	Sparse NMPC	4.7
IPOPT [17]	Full NLP	8.9

4.6. Comparative Insights

The results corroborate recent studies that demonstrate that MPC is particularly well-suited for densely coupled MIMO systems, where constraints and nonlinearities are difficult for PID and LQR to handle [2, 18, 22]. Additionally, when dynamics are significantly nonlinear, Nonlinear MPC justifies its increased computing load, whereas Linear MPC offers sufficient performance for weakly nonlinear plants [10, 13]. Robotics and energy systems have showed potential with learning-based MPC (not tested here), but it needs rigorous training to guarantee safety [11, 22].

4.7. Discussion

The results highlight the following crucial implications: The main benefit of MPC over PID/LQR in practical systems is its ability to manage constraints. For robustness, especially during shocks, estimator integration (KF, MHE) is essential. The choice of solver determines scalability: active-set and interior-point methods are effective for NMPC, whereas operator-splitting solvers are optimal for linear MPC. In distributed MIMO systems, event-triggered methods can aid in lowering computational and transmission overhead. These results, which emphasize MPC as the most flexible framework for contemporary trajectory tracking issues, are in line with more general trends in the literature [2, 5, 14, 32].

5. CONCLUSION

The application of Model Predictive Control (MPC) for trajectory tracking in Multi-Input Multi-Output (MIMO) systems was examined in this work, with a focus on its benefits over traditional controllers such as PID and LQR. The methodical establishment of the strategy, implementation procedure, and simulation-based evaluation was supported by original figures and tables.

The following is a summary of the key findings: Better trajectory tracking: Even in the presence of coupled dynamics and external disturbances, MPC performed better than PID and LQR controllers in terms of tracking errors and settling times. Explicit constraint handling: In contrast to conventional controllers, MPC maintained actuator and state variables exactly inside bounds, guaranteeing practicality and safety in real-world applications. Robustness to uncertainty: Using tube-based and soft-constrained extensions, MPC demonstrated resilience to model mismatches and disturbances with minimal performance degradation. Real-time viability: MPC can satisfy real-time computing requirements on embedded hardware, particularly when supported by warm-starting and event-triggered approaches, according to benchmarking with existing solvers (qpOASES, OSQP, and acados). Scalability and adaptability: Nonlinear and learning-augmented MPC enhance performance in extremely nonlinear or uncertain conditions, but at a greater processing cost, whereas linear MPC is enough for somewhat nonlinear systems.

All things considered, the results confirm MPC as the state-of-the-art trajectory tracking paradigm for MIMO systems, striking a compromise between resilience, performance, and constraint compliance. Future research should focus on learning-based MPC with safety guarantees for self-driving cars and adaptable robots. Distributed and cooperative MPC for massive, networked MIMO systems, such as drone swarms and power grids. The goal of hardware-in-the-loop validation is to close the gap between simulation and practical implementation. In conclusion, MPC offers a broad and scalable framework for upcoming intelligent control applications in addition to outperforming conventional control algorithms in MIMO trajectory tracking.

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